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Cutting through Content Clutter: How Speech and Image Acts Drive Consumer

Sharing of Social Media Brand Messages

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ABSTRACT

Consumer-to-consumer brand message sharing is pivotal for effective social media marketing. Even as companies join social media conversations and generate millions of brand messages, it remains unclear what, how, and when brand messages stand out and prompt sharing by consumers. With a conceptual extension of speech act theory, this study offers a granular assessment of brands' message intentions (i.e., assertive, expressive, or directive) and the effects on consumer sharing. A text mining study of more than two years of Facebook posts and Twitter tweets by well-known consumer brands empirically demonstrates the impacts of distinct message intentions on consumers' message sharing. Specifically, the use of rhetorical styles (alliteration and repetitions) and cross-message compositions enhance consumer message sharing. As a further extension, an image-based study demonstrates that the presence of visuals, or so-called image acts, increases the ability to account for message sharing. The findings explicate brand message sharing by consumers and thus offer guidance to content managers for developing more effective conversational strategies in social media marketing.

Keywords: Consumer Sharing, Brand Communications, Social Media, Speech Act Theory, Rhetoric, Image Acts, Text Mining, Message Dynamics

Social media platforms are rapidly replacing traditional marketing channels as go-to conduits for achieving a variety of marketing objectives, from creating awareness to calling on consumers to buy (Batra and Keller 2016; Kumar et al. 2016). On well-known platforms such as Facebook and Twitter, consumer-distributed (rather than consumer-generated) content can critically increase the reach of brand-generated messages (Napoli 2009). However, even as brands increasingly join social media conversations, the impact on consumers remains distressingly low; an average brand tweet is viewed by just .1% of followers (Marketing Land 2014) and likely gets buried in the vast expanse of big data (Horst and Duboff 2015). The daunting challenge for companies is to produce appealing brand messages with content that is less likely to be buried and more likely to be shared by consumers.

Yet few brand managers have expertise in composing effective online brand messages that prompt consumers to share the content (The Content Marketing Institute 2016). As brands continue to spread more messages, the cacophony of calls to action (e.g., “Check out today’s deal!”) instead has led to decreasing engagement rates, because users simply tune out the noise associated with these messages that tell them what to do (Track Maven 2014). Social media offer little room for variety in message content though (e.g., 280 characters in Twitter), and growing evidence that visuals drive consumer engagement (Hutchinson 2016) requires companies to use verbatim and visual content more strategically. Therefore, it is critical to determine how to use available verbal and image elements effectively to compose dynamic messages that encourage consumer sharing on social media.

Recent theorizing identifies several content-related predictors of such sharing, including positivity (Berger and Milkman 2012; Hewett et al. 2016), interactivity, vividness (de Vries, Gensler, and Leeflang 2012), and media persuasiveness (Stephen, Sciandra, and Inman 2015). Among these valuable insights into online communication though, what is lacking is an integral, theoretically grounded approach to branded message content that

accounts for the joint impact of both verbal and visual content and facilitates firms' participation in social media conversations. Therefore, as a conceptual point of departure, we turn to speech act theory (SAT) (Searle 1969), which is based on the premise that any utterance represents an action, intended to evoke some behavior in the recipient. Speech acts refer to the performative function of communication, in which phrases are indistinguishably interwoven with actions, so the behavior that the message intends to prompt is central (Barinaga 2009). A range of speech acts has been identified as relevant to social media messages, including exerting demands (directive acts), conveying emotions (expressive acts), and offering objective information (assertive acts) (Ordenes et al. 2017; Zhang, Gao, and Li 2011).

In addition to adopting SAT as a foundation for understanding online branded message sharing, we seek to extend it, by incorporating rhetoric (i.e., figures of speech) (Frank 1990), cross-message dynamics (Heracleous and Marshak 2004), and image acts (Bakewell 1998). That is, the character limitations that constrain social media such as Twitter lead to branded content that tends to be replete with figures of speech, similar to poetic language. Rhetorical forms, such as alliteration and word repetition, influence message processing fluency, which in turn can increase readers' attention and positive evaluations (Davis, Bagchi, and Block 2016; Nunes, Ordanini, and Valsesia 2015). Message content and stylistic aspects also perform in concert. However, little is known about whether their interaction in online branded messages (e.g., tweets) increases consumer sharing of those messages. Mounting evidence also suggests that social media conversations consist of streams of consecutive messages, suggesting the need to investigate cross-message aspects (Batra and Keller 2016). We seek to determine their influence on consumer-to-consumer (C2C) message sharing. Finally, though social media messages often contain visual content (Diehl, Zauberaman, and Barasch 2016; Liu, Dzyabura and Mizik 2017), we lack insights into the interplay of speech and image acts

and their impact on C2C sharing. By addressing these gaps, the current study offers four key contributions.

First, we advance knowledge on C2C content sharing in social media by empirically testing a theory-based framework of message content and analyzing the differential impacts of assertive, expressive, and directive messages on consumer sharing. The analysis is guided by automated text analysis, through supervised machine learning and natural language processing tools (Humphreys and Wang 2017).

Second, by acknowledging multiple viewpoints on the impact of rhetoric in relation to speech acts for driving consumer message sharing (McQuarrie and Mick 1996; Schellekens 2013), and in line with recent theorizing on the link between rhetoric and speech acts (Liu and Zhu 2011), we empirically explore the (asymmetric) effects of their combination with assertive, expressive, and directive intentions. We focus on two widely used figures of speech in social media: alliteration and repetition (Davis et al. 2016; Nunes et al. 2015). This study identifies rhetoric as an important boundary condition for the differential effects of message intentions (speech acts) on consumer message sharing.

Third, we add a consideration of cross-message dynamics as integral to social media conversations. Understanding cross-message compositions offers novel, actionable insights into sequences of multiple brand posts in a way that can foster sharing, beyond the effects of the individual messages (Ghoshal et al. 2014). This insight resonates with the emerging view of social media as a dynamic *activity* (Stephen et al. 2017), and the approach is in line with recent calls by Batra and Keller (2016) to address the influence of sequential message intentions (e.g., complementarity vs. consistency) on consumer sharing.

Fourth, we extend SAT to incorporate the role of image acts (Kress and van Leeuwen 2006). In extant consumer research, little attention centers on the compositional elements that reflect the interplay between text and visual content, much less their impact on consumer

sharing. This study is among the first to chart a path to examine how social media content consisting of text and images can be composed effectively to maximize consumer engagement.

Drawing on SAT and its proposed extension, we develop conceptual underpinnings to underscore the interrelatedness of four message elements in social media messages: speech acts, rhetorical styles, cross-message dynamics, and visual elements, such as image acts. This extended SAT-based framework grounds our hypotheses, which pertain to the distinct effects of message intentions, their interactions with figures of speech, the main effects of message dynamics, and the impact of image acts on consumer sharing. We empirically assess our framework with a data set of more than 29,000 tweets and 12,000 Facebook posts by eight and seven major consumer brands, respectively. We conclude by discussing the implications of our findings and sketching directions for further research.

CONCEPTUAL BACKGROUND

Speech act theory provides the groundwork for studying language-in-use (Bagozzi 2007; Ludwig and de Ruyter 2016). Speech acts offer means to convey people's intentions (i.e., illocutionary acts; Austin 1962). Through their performative function, they also can invoke behavioral changes in message recipients (i.e., perlocutionary acts; Searle 1969). Research on speech acts reveals an evolutionary development, from classifying phrases and sentences (e.g., assertives, expressives, directives; Austin 1962, Searle 1969), to integrating rhetoric (i.e., figures of speech; Frank 1990), inter-textual meta acts (e.g., across phrases; Heracleous and Marshak 2004), and image acts (Kress and van Leeuwen 2006). Conceptually, SAT underpins recent consumer research that examines language to understand what people intend to achieve by saying something (Ordenes et al. 2017; Storbacka and Nenonen 2011) or to capture the effects of utterances on audiences (Venter, Wright and Dibb 2015).

The taxonomy of fundamental illocutionary speech acts comprises five forms—assertive, expressive, directive, commissive, and declarative (Searle 1969)—whose use depends on the communication context. In social media contexts for example, content marketers generally try to provide objective information, arouse consumers’ emotions, or call them to action (Kronrod, Grinstein, and Wathieu 2012; Track Maven 2014). Using Searle’s (1976) classification, these three goals parallel assertive, expressive, and directive speech acts. In contrast, commissive and declarative acts are less common in social media settings. Although not linguistic properties themselves, such acts are evinced (and accessible) through speakers’ phrases and sentences (Searle 1969). *Assertive acts* consist of true or false informational phrases, without emotion or valence (Searle 1976) (e.g., “we have launched our new product”). *Expressive acts* are conveyed by speakers through affective phrases (Searle 1976), such as showing appreciation (“Thanks for the award”), offering an opinion (“We love Fridays”), or evoking desires for a situation, product, or service (e.g., “What a great product”). Potentially most important to content marketers are *directive acts*, phrases that issue calls to action (e.g., “Come Monday for the final sale”) or demand information (“What do you think of our latest product?”). *Commissive acts* create a future obligation (e.g., “I promise to deliver”), so providers might issue them (Bilbow 2002) in response to a request (McCallam 2003). But for this study, we focus on the content that brands generate themselves, in which setting they are rare (i.e., 1.6% of all brand messages in our data set included commissive acts). *Declarational acts* involve unilateral decisions, with direct consequences for the recipient (e.g., “You are fired”). Marketers lack the necessary power to perform such declarative acts on consumers in brand messages (and none of the brand messages in our data set were declarative). Considering their lack of use in this context, we exclude commissive and declarative speech acts from the current study.

Instead, we note that compared with assertive and expressive messages, directive messages are the most forward and presumptuous, such that they may be less likely to invoke responses (Austin 1962). Noting the accumulating empirical support for treating speech acts in verbatim messages as reflective of speakers' intentions and predictive of recipients' responses (Ordenes et al. 2017), we mine the phrases and sentences in brands' social media messages for assertive, expressive, and directive acts. We anticipate that assertive and expressive messages will be shared more by consumers due to their ability to facilitate (rather than direct) social media conversations (Carr, Schrock, and Dauterman 2012).

Research in pragmatics also has extended conceptualizations of speech acts to account for rhetoric (Frank 1990). According to Liu and Zhu (2011), there is an inherent link between SAT and rhetoric, which dates back to Austin's (1962) coinage of the term "rhetic act" to refer to the consequential (persuasive) effect of message intentions. Rhetoric refers to stylistic considerations of message constructions, used with an intent to influence receivers' perceptions and interpretations through eloquent, persuasively espoused viewpoints (Aristotle 1991). Rhetorical figures directly influence consumers' interpretations of and reactions to marketing messages (Kronrod and Danziger 2013; McQuarrie, Miller, and Phillips 2013).

Due to this capacity to enhance message fluency, memorability, and overall persuasiveness, alliterations and word repetitions are highly pertinent rhetorical features for marketing communications (Brody 1986; Davis et al. 2016). Because of the excess regularity exhibited by these rhetorical figures, they constitute schemes that violate consumer expectations of sound or word distributions in a message (McQuarrie and Mick 1996). For example, *alliteration*, or the repetition of initial sounds in subsequent words, is common in brand names (e.g., American Airlines), slogans, and advertisements (e.g., McDonald's "big beefy bliss" tagline). Word repetition in a brand message (e.g., "Have a Break, Have a Kit-Kat") similarly enhances the emphasis and memorability of the message (Brody 1986), even

in song lyrics (Nunes et al. 2015). Beyond direct effects, rhetorical figures affect the weight that receivers grant to information or requests in messages (Gill and Whedbee 1997). Therefore, figures of speech signal marketers' intentions to improve message fluency and persuasiveness.

Beyond the acts conveyed within messages, contemporary conceptualizations of speech acts also suggest that cross-message compositions can be designed intentionally to enhance their individual persuasive effects (Heracleous and Marshak 2004). Batra and Keller (2016) propose that marketers should regard messages as continuous, interactive streams. Loda and Coleman (2005) suggest that the right mix of messages is particularly pertinent for engaging consumers in social media conversations. Previous literature distinguishes two main cross-message compositions in social media: complementary or consistent (Batra and Keller 2016). Successive *complementary* messages communicate varied intentions; *consistent messages* repeat the same type of intention. When they vary message content, marketers cater to consumers' different brand-related information needs, whereas repetitions aim to reinforce and facilitate consumer learning (Batra and Keller 2016). Thus, we conceptualize marketers' relative consolidation of the same (variation between) speech acts across several messages as a cross-message act, reflecting their intent to reinforce (complement) prior communication, and we accordingly assess the impacts on subsequent consumer sharing.

Finally, similar to words, images are central to human communication (Bakewell 1998). With the rise of social media platforms, shared images have become increasingly important in C2C communications (Diehl et al. 2016); in some case, images even appear to surpass text as a medium of choice in social media conversations (Kane and Pear 2016). Images can do more than represent reality descriptively, so they also can be categorized as intended actions (Kress and van Leeuwen 2006). Advertising research affirms that images are powerful tools, capable of persuading consumers to act or buy (Pieters and Wedel 2007), and

an intricate interplay exists between text and pictorial elements in the same advertisement (Pieters and Wedel 2004). Increased attention to one ad element might be at the expense of or else spill over to other ad elements (Pieters and Wedel 2004). The wealth of visual, brand-related content on social media necessitates studying its unique impact on consumer sharing, as well as its joint implications with verbatim speech acts that appear in the same message.

HYPOTHESES

Implications of Speech Acts for Consumer Sharing

Speech acts, manifest in both phrases and sentences, vary in the extent to which they elicit responses (Austin 1962; Searle 1969). Directive acts may appear more authoritarian (Dalton-Puffer 2005), signaling the dominance of the message sender over the recipient (Dillard and Shen 2005). Other arguments indicate that because directive speech acts generally are more conclusive, they leave less room for ambiguity and discussion relative to assertive or expressive speech. In addition, assertive and expressive speech acts require less processing, because they are salient and entertaining (Nastri, Pena, and Hancock 2006). Therefore, and in light of findings that show that consumers prefer non-forceful (e.g., “I’m loving it” from McDonald’s) over imperative (e.g., “Just do it!”) brand messages (Kronrod et al. 2012), we recognize the need to examine differential impacts of various speech acts on consumers’ message sharing. In particular, according to Carr, Schrock, and Dauterman’s (2012) linguistic analysis of status messages on Facebook, speech acts primarily feature expressive and assertive messages. Thus the ability of assertive and expressive messages to facilitate (rather than direct) conversations on social media may make consumers more prone to share them (Carr, Schrock, and Dauterman 2012). Berger and Milkman (2012) also find

that content positivity and arousal (i.e., expressive acts) increase sharing of news media articles among consumers, whereas Stephen et al. (2015) suggest that social media messages designed to direct and issue calls to action are unlikely to be shared. Consumers primarily exchange social media content to establish and maintain relationships with their peers (Batra and Keller 2016), so brand messages that facilitate interaction and debate, rather than require a specific action, should be more widely shared. We predict that assertive and expressive brand messages (which facilitate conversation) lead to more consumer sharing than directives (which dictate conversation and modify receivers' behavior):

H₁: Consumers share expressive or assertive brand messages more frequently than directive brand messages.

Joint Implications of Speech and Rhetoric for Consumer Sharing

The inseparability of content and style in communication (Ludwig et al. 2013) stems from the inherent association between speech acts and rhetoric (i.e., alliteration and repetition) (Austin 1962). In marketing practice, figures of alliteration and repetition appear in various brand message goals; alliterations and word repetitions increase message persuasiveness by generating pleasant rhythmic effects or emphasizing its content, respectively. The use of alliteration in social media brand messages can be matched with assertive (e.g., “deal of the day”), expressive (“Functional, fashionable, formidable”), or directive (e.g., “Start saving now!”) goals. Word repetition similarly can be matched with assertive (e.g., “New year, new car”), expressive (e.g., “It is amazing if things don’t go amazing”), and directive (e.g., “Tweet your ingredients and we will tweet back!”) goals.

In recognition of the various manifestations of speech acts and rhetoric, we identify the need to theorize about the joint effects of message content and style. Although McQuarrie and

Mick (1996) posit that the persuasive impact of rhetoric is independent of message intention (i.e., type of speech act), Schellekens et al. (2013) suggest that the influence of rhetorical figures varies across communication objectives. In other words, there is an ongoing debate about the joint influence of different types of speech acts and rhetoric. Adding to the complexity of this debate, alliteration is commonly conceptualized as unidimensional (Davis, Bagchi, and Block 2016), whereas word repetition can take multiple forms (e.g., antimetabole, antithesis, anaphora; McQuarrie and Mick 1996) or appear as an aggregated parameter (Nunes et al. 2015). Finally, it remains unclear whether the specific constraints of social media platforms (e.g., 280 characters in Twitter) have unique influences on consumer message sharing (Schweidel and Moe 2014). That is, a general consensus indicates that rhetorical figures amplify the persuasive power of speech acts (Liu and Zhu 2011), but there is a general lack of theoretical insights regarding whether amplification occurs independently of (1) the speech act and corresponding message intentions, (2) the type of rhetoric (i.e., alliteration vs. word repetition), and (3) social media platform constraints. In this sense, rather than formally stating a hypothesis, we explore the joint effects of speech acts and rhetoric (alliteration and word repetition) on message sharing by investigating the following research question:

RQ1: Does the joint impact of speech acts and rhetoric on message sharing differ across speech acts (assertive, expressive, directive), figures of speech (alliteration, repetition), or social media platforms (Twitter, Facebook)?

Implications of Cross-Message Speech Acts for Consumer Sharing

Prior events influence consumers' evaluations of subsequent events (Ghoshal et al. 2014). In marketing communications, the way messages build on one another can determine their success in terms of persuading consumers, building brand equity, or driving sales (Batra and Keller 2016). Consistently communicating the same persuasive message facilitates

learning but also tends to be perceived as dull and non-engaging by consumers (Kocielnik and Hsieh 2017). Instead, messages can be mixed to achieve complementarity, such that the effects of consumer exposure to one message might be enhanced if consumers previously have been exposed to a different type of message (Batra and Keller 2016). Consumers may have a general preference for message intentions that facilitate conversation or invite discussion, but in sequence of messages, there may be a need to switch up the intentions to break the monotony and cut through the clutter. Imagine, for example, a brand tweet that asserts: “We are developing new ways to move through life,” followed by another tweet that directs consumers: “We’ve got an all-new vehicle announcement coming today at 12:00. Check it out here.” Consistency enables message recipients to know what to expect; complementary sequences might result in greater sharing, by drawing recipients’ attention to their novelty rather than boring them with the same message (Kocielnik and Hsieh 2017). This effect may be especially relevant for attempts to engage a broad consumer audience (Batra and Keller 2016). We thus hypothesize:

H₂: Consumers share more frequently brand messages preceded by complementary message sequences than by consistency message sequences.

Image Acts and Consumer Sharing

Social media messages are generally multimodal, such that they contain both text and images (Mazloom et al 2016). Both elements can signal message intentions. As evidenced by Bateman, Wildfeuer and Hiippala (2017), considering text as the only driver of sender intentions in social media messages ignores that images can also convey intentions. Thus, similar to speech acts, images acts can be used to convey people’s intentions through their performative function (Bakewell 1998; Kress and van Leeuwen 2006). Evidence from

previous studies also suggests that exposure to images influences people's evaluations and judgments of attitude objects, such as brands and products (Pieters and Wedel 2007). That is, simply seeing an image together with a social media brand message might be sufficient to influence thoughts and behaviors (Poor, Duhachek, and Krishnan 2013). Image acts can range from offering information that allows for multiple interpretations to directing specific actions (Kress and Van Leeuwen 1996). For example, a tweet that simply shows information images of food items (figure 1, information) leaves the interpretation to the viewer. In contrast, action images portraying a person pointing to a food item require the viewer to direct his or her attention to that particular object (figure 1, action). In line with the hypothesized link between (directive vs. assertive and expressive) speech acts and consumer sharing (H_1), we posit that information images, rather than action images, facilitate social media conversations and are more prone to be shared. Accordingly,

[Insert figure 1 about here]

H₃: The more an image in a social media message directs consumer action, the less the message is shared.

Joint Implications of Speech and Image Acts

Beyond their individual effects, text and image message acts are frequently combined within the same brand message (i.e., tweets or posts), warranting further investigation into their joint effect on consumer sharing. Previous research confirms that textual and image elements within the same advertisement are interdependent, with distinct explanatory power (beyond their individual effects) for consumer attention and reactions (Pieters and Wedel 2004). Similar to the hypothesized phenomenon of cross-message consistencies (H_2), conveying the same act through both image and text within the same message is likely to be

perceived as consistent and therefore less novel. For example, if the text of a brand tweet calls consumers to action, including an action image as well likely is unsurprising to consumers (Dillard and Zhen 2005). If the text and visual acts instead are complementary (e.g., assertive text accompanied by action image), their combination may evoke greater attention and promote consumer sharing. Thus, we predict that messages containing text and image acts that are complementary lead to more consumer sharing than messages that contain text and visual elements that are consistent. We hypothesize:

H4: Images portraying a greater degree of action are more shared in combination with an assertive or expressive speech act, rather than in combination with a directive speech act.

INTENTIONS, STYLE, AND SEQUENCES IN POST AND TWEET STUDIES

Research Setting

To examine the differential effects of brand message intentions, style, and sequences on message sharing, we collected data sets from two leading social media platforms, Facebook and Twitter. Facebook does not restrict the number of characters; Twitter allowed for only 140 characters per message at the time of our study.¹ Arguably then, brand content managers must design their Twitter messages especially carefully to encourage consumer sharing. The data set included 12,374 Facebook posts and 29,413 brand-generated tweets by eight brands across different industries between October 2015 and May 2017. We discuss both sub-studies (Facebook and Twitter) simultaneously.

¹ In 2017, subsequent to our data collection, Twitter increased the number of characters allowed in a single message, from 140 to 280.

We focused on consumer brands, whose communication, goals, channels, appeals, and measures of success differ from those for messages targeting business clients (Agnihotri et al 2016). To increase generalizability, the sample covers several industries and both products and services, such as food, manufacturing, retailing, and hospitality. For each sector, we include an industry leader as a representative brand, except for retail, for which retailers' widespread presence in social media requires consideration of multiple subcategories. By investigating the industry leader, we gain insights into a social media strategy that is broadly accepted by consumers and potentially copied by other brands; in contrast, a niche player might opt for an unconventional strategy to garner attention, but such an approach would likely be inappropriate for most firms. Table 1 contains descriptive statistics related to the brands we study (7 for Facebook and 8 for Twitter).

[Insert table 1 about here]

Our final selection includes brands from the food (standard industrial classification [SIC] 2000), manufacturing (SIC 3000), retailing trade (SIC 5200), and hospitality (SIC 7000) sectors and excluded industries such as mining (SIC 1000) or healthcare services (SIC 8000). We then used SocialBakers.Com to identify brands and industries with a strong social media presence on both Facebook and Twitter, set up specifically to engage end consumers. With this step, we chose the following brands: Coca-Cola (SIC 2000), Ford (SIC 3000), Walmart and Tesco (both SIC 5300 and SIC5400), McDonald's (SIC 5800), Amazon (SCI 5900), and Disney Parks (SIC 7000). We only collected data about the Nike Store (SIC 5600) from Twitter, because it did not maintain a parallel account on Facebook.

Measures

In line with previous marketing research, we operationalize consumer message sharing

as the number of retweets or shares on Facebook (Gong et al. 2017). Specifically, we calculated the number of shares that an original brand tweet or Facebook post received. Every brand message in our data set had been shared for at least seven days, reflecting the period when most consumer engagement with a social media message happens (Lee, Hosanagar, and Nair 2016). In addition, as a robustness check, we used the number of favorites (Twitter) or likes (Facebook) as a dependent variable. This measure represents weaker customer engagement (Peters et al. 2013), but we expect similar results (see the appendix).

With a supervised machine learning approach, we classified the brand-generated messages according to three message intentions: assertive, expressive, or directive. In line with Humphreys and Wang (2017), in this supervised learning approach, humans perform coding during the training and testing phase, to ensure that the automated text classification is in line with the guidelines defined by SAT. Supervised learning involves preparing the data for machine learning, then training and testing an automated text classifier with a human-annotated sample (which provides an accuracy value from a holdout sample), and finally making predictions about the non-annotated data (Zhai and Massung 2016). As the final output, we sought to obtain three dummy variables, representing each message intention.

Using Knime Analytics' embedded text processing tools (Tursi and Silipo 2018), we prepared the data for machine learning. First, in line with our conceptual development and recent research (Ordenes et al. 2017), we assess message intentions at a sentence level, so we split each Facebook post and tweet into sentences, resulting in 29,421 (average of 2.37 sentences) on Facebook and 60,718 unique sentences (average of 2.06 sentences per tweet) on Twitter. Second, sentences including a question mark usually demand information (e.g., "Who will you take your next trip with?") or frame another message intention (e.g., "Visiting Boston? Here are 10 reasons to stay at this hotel"). Questions also can be identified easily by retrieving sentences with question marks at the end (".*\?.*"), so we did not need coders to

annotate them. When the questions accompany another speech act (assertive, expressive or directive), we used a dummy variable to signal a framing effect; brand messages that include a single question are by definition directive, because they represent a request for information (Searle 1976).² We confirmed that this operationalization did not produce collinearity between directive messages and questions (Facebook $r = .13$; Twitter: $r = .11$). Third, we used three regular expressions (Ordenes et al. 2017) to exclude sentences that only contained a URL, hashtag (#), or “at” signifier (@). Specifically, we used the following list of expressions: $(\text{htt}[\wedge]^*); \# \backslash \text{w}+; (\text{htt} \# \backslash \text{w}+ | @ \backslash \text{w}+) \backslash \text{b} . \{0,2\} (\text{htt} \# \backslash \text{w}+ | @ \backslash \text{w}+) . *$

In the supervised learning approach, two independent coders manually annotated a subset of 5,790 sentences as assertive, expressive, or directive messages (Krippendorff’s alpha = 86.7%; disagreements resolved through discussion).³ They identified 2,315 sentences as assertive (39.9%), 507 as expressive (8.7%), and 2,968 as directive (51.2%). Next, using Zhang et al.’s (2011) procedure, we automated the classification of brand messages as speech acts. This process required three steps: (1) identify words to use as predictors of message intentions, (2) apply a machine learning algorithm to predict the coder’s classification according to the word predictors, and (3) assess the accuracy of the algorithm for multiple holdout samples (cross-validation).

We began by selecting only (1) sentiment words (using SentiWordNet, Baccianella, Esuli, and Sebastiani, 2010; and Subjectivity Lexicon, Wilson, Wiebe, and Hoffmann 2005); (2) the most frequent unigrams, bigrams, and trigrams; (3) vulgar words; and (4) Twitter operators (# and @) (see also Zhang et al. 2011). All these words conserved part of speech

² We tested the model both with and without questions as a control variable, and the results remain consistent. We thank an anonymous reviewer for suggesting this test.

³ We created the machine learning tool using Twitter sentences only, but it can make accurate predictions for both Twitter and Facebook. First, the average words per sentence are 10.3 and 14.3 on Twitter and Facebook, respectively, suggesting sentences of similar lengths. Second, the selected brands are the same on Twitter and Facebook, so we can expect similar word patterns. Third, from a text modeling approach, it is better to develop a machine learning tool using shorter sentences, then extend it to longer sentences, rather than the opposite.

(POS) tags. Then, to avoid the unnecessary challenge of an extremely large number of word predictors that are not substantively different in a semantic sense, we converted them into their root forms (e.g., words such as “fishing,” “fisher,” and “fished” all were converted to “fish”). This step resulted in 56,674 unique words. Using a support vector machine (SVM), which offers a semiparametric technique widely used in computer science literature (Cui and Curry 2005), we then trained and tested the classification tool to predict sentence intentions in brand tweets and Facebook posts. Although relatively less applied in marketing and consumer research, SVM has demonstrated utility for prediction (cf. explanation) tasks (Cui and Curry 2005). The support vectors consist of 56,674 unique words (1 if the word is present, 0 if not). We used them to predict the message intentions of each brand message sentence in a linear, SVM-based, one-against-one approach (Chang and Lin 2011). The classification problem involves $\{x_i, y_i\}$, where x_i is the support vector for the i th message sentence, and $y_i \in \{-1, +1\}$ is the corresponding label (assertive, expressive, or directive). The weight of the support vectors is labeled w , and the SVM is formulated to find an optimal hyperplane $w^T \phi(x_t)$ that maximizes the distance between messages, pertaining to a message intention class (+1) or not (-1). Accordingly, we minimize the following equation:

$$\begin{aligned} \min w, b, \xi \quad & \frac{1}{2} w^T w + C \sum_i^l \xi, \\ \text{subject to } & y_i(w^T \phi(x_i) + b) \geq 1 - \xi_i \text{ and } \xi \geq 0, i = 1, \dots, l, \end{aligned}$$

where $C > 0$ is the regularization parameter of the error term (ξ), and b is a constant. Finally, to determine the accuracy of the SVM for classifying brand message sentences, we used 80% of the human annotated data to train the SVM classifier and then tested it on the remaining 20% (holdout sample). With a 10-fold cross-validation (i.e., 10 different training and testing samples, from the human annotated sample, to avoid overfitting), we achieved satisfactory accuracy of 87.7% (table 2), in line with previous research (Zhang et al. 2011). The appendix

contains a detailed visualization of the Knime workflow used to classify message intentions at the sentence level.

[Insert table 2 about here]

After implementing the sentence classification on the entire data set, we noted that 22.8% and 13.2% of Facebook posts and tweets, respectively, included at least two different brand message intentions (e.g., “Everybody loves a good #Rollback! [expressive] Come in now and save on TVs, treats and more [directive]”), so we needed a classification rule for these cases. Following the inherent hierarchy of speech acts (Austin 1962), we operationalized assertive intentions as the lowest and directive intentions as the highest level of dominance. In the preceding example, the expressive intention (“Everybody loves a good #Rollback!”) is subordinate to the second, directive intention (“Come in now and save on TVs, treats and more”), so we classified the message as directive. The output of this process was three dummy variables, each representing a message intention (assertive, expressive, or directive). In addition, we included another dummy variable to control for whether the social media message included multiple (different) message intentions (1) or not (0).

We next operationalized rhetoric according to the syntactical patterns that depict word repetitions and alliterative sounds, using several natural language processing techniques (Humphreys and Wang 2017). Alliteration occurs when two subsequent or closely connected words start with the same phonemes (Davis et al. 2016). The “deal of the day” is an alliteration, despite the presence of simple words between “deal” and “day.” We conducted the same preprocessing steps that we applied for word repetition. As detailed in the appendix, we used 30 regular expressions to find alliteration. For example, closely connected words starting with “f” (e.g., “fun”) and “ph” (e.g., “phone”) alliterate; we used the regular expression (REGEX) “(\bf\w+|\bph\w+)\s(\bf\w+|\bph\w+)” to identify this pattern in a sentence. Words starting with letters that have multiple sounds, such as “c” (e.g., “cake” vs.

“Cesar”) were not considered alliterations, and we used eight regular expressions to exclude them from the retrieved set (see the appendix). We specified an alliteration only if the words were different from each other (if they were the same, they would be classified as repetition). Finally, we computed the total number of alliterations within a brand message and used this variable in our model; this measure ranged from one (e.g., “gaming for good”) to four (“Fall fun, family-friendly activities for autumn”). To validate this approach (McQuarrie and Mick 1996), we used the same variable but considered only alliterations of three or more words; the results did not change.

To identify word repetitions in a brand message, we preprocessed the data by converting everything to lower case, excluding stop words⁴ (e.g., “the,” “to,” “it,” “is”), and splitting the messages into sentences. Finally, we deleted punctuation within a sentence, as is common in natural language processing (Kim and Kumar 2017). Using a bag-of-words approach (Zhai and Massung 2016), we identified the number of word repetitions within a message, computed the total number of repetitions within a brand message, and used this variable in our model. The repetitions ranged from one word (e.g., “Normal potatoes are the new potatoes”) to five (“We really really really really really like potatoes”).

In line with Ordenes et al. (2017), we operationalized message sequences as compositions of at least three subsequent messages (tweets or Facebook posts). We used the Herfindahl-Hirschman index to assess the level of concentration (consistency) in the message intention, preceding a focal brand message, as follows:

$$Consistency_i = \left(\frac{\sum_{l=-2}^1 Assertive_i}{3} \right)^2 + \left(\frac{\sum_{l=-2}^1 Expressive_i}{3} \right)^2 + \left(\frac{\sum_{l=-2}^1 Directive_i}{3} \right)^2 ,$$

where *Assertive_i*, *Expressive_i*, and *Directive_i* are dummy variables indicating whether a message was classified as each type (1) or not (0). Then we computed the sum of the squared

⁴The list of stop words we used is available at <http://www.ranks.nl/stopwords>. Most of them are commonly repeated words, without stylistic intention, such as “the” or “to.”

relative frequency per message type, resulting in a measure of concentration that varies from very diversified (0) to very concentrated (1). Table 3 provides the variable means, standard deviations, and correlations; we find no collinearity issues (Mela and Kopalle 2002). Due to the substantial variation in the time gaps (in hours) between subsequent brand messages across brands (Facebook $M = 12.4$, $SD = 25.6$; Twitter $M = 6.1$, $SD = 14.4$), we control for the average time gaps across the previous three messages.

[Insert table 3 about here]

Control Measures

Several content and framing characteristics might influence consumer message sharing too. Accordingly, we account for message positivity with the Dictionary of Affect in Language (DAL; Whissell 2009; Yin, Bond, and Zhang 2017), and in line with Berger and Milkman (2012), we also computed it using the Linguistic Inquiry and Word Count dictionary (Pennebaker et al. 2007). The results did not change in significance or direction, so we report only the findings from the DAL.

We include the hour of the day the message was posted, whether it appeared on the weekend (Cvijikj and Michahelles 2013), and the number of hashtags included in the message (Stieglitz and Dang-Xuan 2013). Noting findings by de Vries and colleagues (2012), we control for the presence of questions (to assess the level of interactivity of a post), images, videos, and links (i.e., URLs). We identify messages that are retweets or shares from another account; simply by their status of having already been shared, these messages may have a higher probability of being shared again (e.g., Coca-Cola could share a message from one of its sponsored events). In the Facebook data, we also control for the feature “album” (1 = post pertaining to a photo album; 0 = not pertaining to a photo album); this feature is not available on Twitter.

Model Specifications

In line with previous research and the unique characteristics of social media networks, we ran two separate models for the Facebook and Twitter data sets (Schweidel and Moe 2014). Thus our model can provide granular insights into language use in different social media networks. The number of shares or retweets in our data sets follows a negative binomial distribution, with an over-dispersed count around the mean (Heimbach and Hinz 2016). Comparing the model fit of a negative binomial model with an alternative Poisson regression, we find a significantly better log-likelihood for the negative binomial model (Facebook: $\chi^2 = 390.862$, $p < .01$; Twitter: $\chi^2 = 480.967$, $p < .01$). We include brand fixed effects to account for heterogeneity in content managers' ability and expertise in creating daily content (Kopalle et al. 2017). Moreover, we use a lagged dependent variable (share/retweet count₋₁) in the predictor set, so that the model can account for carryover effects from one share/tweet to the next (Franses and van Oest 2007). With this lagged term, we also rule out the effect of the virality of a previous tweet, which likely influences the visibility of the next share/tweet. Finally, following Stephen et al.'s (2015) implementation of Petrin and Train's (2010) control function method, we assume an endogenous, dynamic relationship between subsequent content variables. Control functions are conceptually similar to instrumental variables, such that our model can account for the effect of managers' previous content decisions on the success (e.g., share or retweets) of subsequent posts. Each control function is a regression, in which the main content variable is regressed on its lag and the lags of all other main content variables.

We applied the control functions sequentially. In the first stage, we estimated the residuals for a subset of control functions, based on the content and control variables. Then in

the second stage, we integrated the residuals into our main model to test the hypotheses. The control functions included (1) the message intentions and rhetorical figures variables, which represent our main content effects, and (2) the control variables associated with the degree of positivity, questions, hashtags, picture, video, and URL, in accordance with their demonstrated relevance in previous social media research. For the content variable $x_{k,ij}$ for example, k indexes the content or control variable (1 to L), i indexes the brand (1 to N), and j indexes the post (1 to J_i). Each control function takes a similar form, and its estimation shifts with the variable measurement level. For example, the control function (k) for the control variable positivity would be a linear regression model, because the variable is on a ratio scale:

$$\begin{aligned} \text{Positivity}_{ij} = & \alpha + \beta_1 * D.\text{Assertive}_{i,j-1} + \beta_2 * D.\text{Expressive}_{i,j-1} + \beta_3 * \\ & \text{Alliteration Count}_{i,j-1} + \beta_4 * \text{Repetition Count}_{i,j-1} + \text{Positivity}_{i,j-1} + \text{Question}_{i,j-1} + \\ & \text{Hashtag}_{i,j-1} + \text{Picture}_{i,j-1} + \text{Video}_{i,j-1} + \text{URL}_{i,j-1} + \varepsilon_{i,j}. \end{aligned}$$

In this case, positivity is estimated using the lagged values of the main content and control variables (on Facebook, we also added the album control variable). The assertive, expressive, question, image, video, and link variables are binary, so we used probit models to estimate them. Alliteration and repetition are count variables, such that we used Poisson models to estimate them. After estimating all control functions, we computed the residuals for each model and included these values in the second-stage response functions (Danaher et al. 2015). Including the first-stage residuals in the estimation of the main model enables us to decompose the effects of our independent variables, as endogenous or exogenous. As Stephen et al. (2015) caution, excluding the control function residuals from our main model would result in biased parameter estimates for the effects of the various content characteristics on message sharing. We do not report the control functions due to space limitations, but they are available in a web appendix, along with the results when we exclude the control function.

We used three models to test our hypotheses. Model 1 tests for differences in sharing behavior pertaining to assertive and expressive, relative to directive, messages (i.e., directive

message is the baseline dummy). Model 2 analyzes the interaction effects of figures of speech and message intentions (directive is the baseline for the interaction). Model 3 studies the effects of consistency sequences (Herfindahl index) and a control variable regarding the average time gap across the three messages. The group-level covariates are consistent across all models, to ensure comparability (2log-likelihood). In summary, the model for the share variable (share of posts or retweets) is:

$$\begin{aligned} \#Share_i = \exp(\alpha_0 + \beta_1 * \#Share_{i-1} + \beta_2 * D.Assertive_i + \beta_3 * D.Expressive_i + \\ \beta_4 * Alliteration_i + \beta_5 * Repetition_i + \beta_6 * D.Assertive_i * Alliteration_i + \beta_7 * D.Expressive_i * \\ Alliteration_i + \beta_8 * D.Assertive_i * Repetition_i + \beta_9 * D.Expressive_i * Repetition_i + \\ \beta_{10} * Sequence\ Consistency_i + \beta_n \theta_n + \tau_i + \alpha_k + \epsilon_{ij}), \end{aligned}$$

where $\beta_n \theta_n$ represents the control variables and their respective coefficients, τ_i indicates the control residuals from the control functions, and $\alpha_k + \epsilon_{ij}$ are the brand fixed effects and error term, respectively.

With a hierarchical approach, we compare the four models by computing chi-square differences from the 2log-likelihood values. This test confirms that rhetoric and sequences each add explanatory power to model 1 (i.e., message intentions $p < .01$). We use estimates from model 3 (table 4), which includes all hypothesized effects, to present the results.

Hypotheses Tests

First, in line with H_1 , model 3 confirms that consumers share significantly more expressive and assertive messages than directive ones (table 4). This effect is consistent for the coefficients obtained from Facebook ($\beta_{Assertive} = .018$, ns; $\beta_{Expressive} = 8.591$, $p < .01$) and Twitter ($\beta_{Assertive} = .284$, $p < .01$; $\beta_{Expressive} = 1.448$, $p < .01$).

Second, the exploration of the joint effects of speech acts, figures of speech, and social media platforms reveals the differential results. Word repetition exhibits a significantly more

negative interaction effect with assertive and expressive than with directive messages on Facebook ($\beta_{\text{Assertive} \times \text{Repetitions}} = -.146, p < .01$; $\beta_{\text{Expressive} \times \text{Repetitions}} = -.736, p < .01$), but the opposite effect arises on Twitter ($\beta_{\text{Assertive} \times \text{Repetitions}} = .17, \text{NS}$; $\beta_{\text{Expressive} \times \text{Repetitions}} = .386, p < .01$). Alliteration has a significant, positive interaction with assertive and expressive messages on Twitter ($\beta_{\text{Assertive} \times \text{Alliterations}} = .191, p < .01$; $\beta_{\text{Expressive} \times \text{Alliterations}} = .606, p < .01$). On Facebook, alliterations have a more positive effect when combined with expressive than with directive messages, but not with assertive messages ($\beta_{\text{Assertive} \times \text{Alliterations}} = -.043, \text{NS}$; $\beta_{\text{Expressive} \times \text{Alliterations}} = .179, p < .01$). These results highlight the differences between the more fluent effects of repetition and the more subtle effects of alliteration.

Third, we find support for our predictions regarding message sequences. That is, complementary sequences have a stronger positive effect on consumer sharing than consistent ones, in support of H₂. A greater concentration of message intentions (e.g., three brand messages signaling the same intention) has a negative effect on message sharing on Facebook ($\beta_{\text{Consistency}} = -.174, p < .01$) and Twitter ($\beta_{\text{Consistency}} = -.370, p < .01$).

Fourth, among the control variables, message positivity has a positive and significant relationship with consumer message sharing on Facebook ($\beta_{\text{Positivity}} = .447, p < .01$), but it is not significant on Twitter ($\beta_{\text{Positivity}} = .014, \text{NS}$). The uses of questions and pictures significantly increases message sharing, whereas messages posted during the weekend and with more hashtags are less often shared, on both Twitter and Facebook. The other control variables indicate distinct effects for Twitter and Facebook, and posts within an album prompt less sharing on Facebook. Finally, all brand fixed effects differ significantly from the baseline.

[Insert table 4 about here]

SPEECH AND IMAGE ACTS, STUDY EXTENSION

To assess the relevance of our speech act framework in increasingly visual social media contexts (table 5), we also consider the implications of image acts and their interplay with speech acts. As prior research on image acts shows (Kress and van Leeuwen 2006), the intentions communicated by images range from offering information to directing action. To the best of our knowledge, no developed scale exists to assess the degree of action expressed by social media images. Therefore, we operationalize such a measure, in two steps.

[Insert table 5 about here]

First, we selected a stratified random sample (by brand) of 200 images from the overall data set. Approximately 27% of the images accompanying a social media post in our data were videos. Accordingly, we created a scraping tool to extract the first screenshot of an image that appears in each video. To account for the difference between still pictures and videos, we also included a dummy image variable (1 = image is a picture; 0 = image is a video). Using extant definitions of information and action (Kress and van Leeuwen 2006), we asked two research assistants to annotate each image with the following instructions:

Images of offer provide visual information to the viewer (for example: the image of a product, landscape, or a person working and NOT looking at the viewer). Images of demand require a response from the viewer (for example: a person staring to the viewer, waving hand to the viewer, or pointing a direction to the viewer). Please rate from 1 to 7 how the image is perceived, 1 = “offer” and 7 = “demand”

After the coders finished the annotation, they resolved any disagreements through discussion. A subsample of 50 images provided an example set for the next step of the coding process. Figure 1 includes examples of images annotated as strongly offering information or strongly directing action.

Second, considering the many images in our data set, we decided to perform the analysis only on the last year of data, May 1, 2016, to May 1, 2017, which featured 9,215 images. We used Upwork (2017), an online labor market, to hire image annotation specialists. Of 29 job applications received, we selected 11 people, based on their previous experience

with similar jobs and their job success rate. On the basis of the set of images annotated in step 1 by the research assistants, we developed a corroboration test of 50 images that we asked all candidates to complete. The 8 candidates who achieved the highest agreement scores (Krippendorff's alpha) continued with the annotation. Two coders, supervised by the first author, coded each image, so each pair coded 2,303 images (9,215) approximately, and the overall correlation was high, at .66. Therefore, we computed the mean value provided by the two coders and used it as our independent variable.

Social media images also might include some textual elements (Pieters and Wedel 2004), so we controlled for the presence of any text in the image (1 = included readable text; 0 = did not include readable text). Figure 2 provides example images that include text. Inter-coder reliability, measured by Krippendorff's alpha, reached 86%, and disagreements were resolved through discussion between the two coders.

[Insert figure 2 about here]

The modeling approach mimics that for the main study, adjusted to the subsample data of images over one year.⁵ In a hierarchical approach, model 4 replicates model 3 (from the main study) with the subsample, model 5 includes the information–action variable, and model 6 adds the interaction with speech acts (using directives as a baseline). A control variable, text on image, also appears in models 5 and 6. The equation is as follows:

$$\begin{aligned} \# Share_i = & \exp(\alpha_0 + \beta_1 * \#Share_{i-1} + \beta_2 * D.Assertive_i + \beta_3 * D.Expressive_i + \beta_4 * Alliteration_i + \\ & \beta_5 * Repetition_i + \beta_6 * D.Assertive_i * Alliteration_i + \beta_7 * D.Expressive_i * Alliteration_i + \beta_8 * \\ & D.Assertive_i * Repetition_i + \beta_9 * D.Expressive_i * Repetition_i + \beta_{10} * Sequence Consistency_i + \beta_{11} * \\ & Information Action_i + \beta_{12} D.Assertive * Information Action_i + \beta_{13} D.Expressive * \\ & Information Action_i + \beta_n \theta_n + \tau_i + \alpha_k + \epsilon_{ij}). \end{aligned}$$

In line with H₃, model 6 confirms that consumers share messages less when they

⁵ The entire data set of messages in this period included 4,284 and 8,287 for Facebook and Twitter, respectively. Of these, only 2,214 and 6,996 messages, respectively, included images. The results of model 4 do not vary substantially compared with the same model applied to the data without images.

contain images that are more action than information oriented (table 6). This effect is consistent across both Facebook ($\beta_{\text{Information Action}} = .07, p < .01$) and Twitter ($\beta_{\text{Information Action}} = .07, p < .01$). The findings also support H₄, revealing an interaction effect between message intentions at the text and image levels. A stronger action image has a more positive effect when the text message is assertive or expressive rather than directive (Facebook $\beta_{\text{Assertive} \times \text{Information Action}} = .088, p < .01$, $\beta_{\text{Expressive} \times \text{Information Action}} = .117, p = .06$; Twitter $\beta_{\text{Assertive} \times \text{Information Action}} = .038, p < .01$, $\beta_{\text{Expressive} \times \text{Information Action}} = .130, p < .01$). In addition, the presence of readable text in social media images increases message sharing (Facebook $\beta_{\text{Text on Image}} = 0.19$; Twitter $\beta_{\text{Text on Image}} = .29, p < .01$).

[Insert table 6 about here]

DISCUSSION

By drawing on speech act theory and conceptual extensions including rhetoric, cross-message dynamics and image acts, this study contributes to consumer research on social media sharing by enhancing understanding of the within- and cross-message acts exhibited in social media brand communication. We delineate a theory-based framework to characterize brands' message intentions, then empirically assess the relationships using advanced text mining techniques and image annotation in two prominent social media networks, Facebook and Twitter. Accordingly, this study offers four primary implications for extant research into consumer message sharing. The results of the analysis across both Facebook and Twitter data sets are summarized in table 7.

[Insert table 7 about here]

First, prior research has established that framing characteristics relate to message sharing, but it has not provided a field test of a theory-driven framework. With a systematic

review of marketing and linguistics literature, we develop such a framework. To distill brand message intentions, we text-mined verbatim messages (Humphreys and Chang 2017; Zhang et al. 2011),⁶ and we thereby identify differential effects. Directive messages, or explicit calls to action, induce less consumer sharing than assertive (informational/factual) or expressive (emotional) messages. Our findings, across both Facebook and Twitter, resonate with previous research that indicates that messages with socio-emotional intentions are more likely to be exchanged (Carr et al. 2012). However, on Facebook we do not find evidence of a more positive effect of assertive compared with directive messages. We posit that this result reflects Facebook's function as a more emotional social network, focused on maintaining relationships with friends, family, and followers. On Twitter, assertive or factual content is more readily exchanged, and many messages aim to spread information (Visual Scope 2017). Thus, in contrast with firms' frequent uses of directive messages (Kronrod et al. 2012), our findings recommend that managers who want their brand content to be shared by consumers need to use messages that facilitate, rather than dictate, consumers' social interactions online.

Second, marketers use stylistic subtleties such as letter repetitions, sentence structures, or word (ir)regularities to make brand messages more persuasive (McQuarrie and Mick 1996), so we leverage rhetoric literature (Liu and Zhu 2011) and explore the effects of speech acts and rhetoric (alliteration and word repetition) on consumer sharing. We obtain mixed findings, which inform the ongoing debate about the joint influence of different types of speech acts and rhetoric. In line with Schellekens et al. (2013), who argue that the persuasiveness of rhetorical figures varies with communication objectives, we find that assertive and expressive (cf. directive) messages that feature alliteration trigger greater consumer sharing on social media platforms. In general, alliteration appears to improve the pleasant and rhythmic effects associated with the social, colloquial interactions encouraged by

⁶ The text mining code for the speech act (message intention) classification and identification of figures of speech is available on request.

assertive and expressive messages (Brody 1986; Leech 1969). In an intriguing exception though, alliteration does not influence the effects of assertive messages in Facebook, suggesting some boundary conditions. In addition, for Facebook messages, word repetition evokes less consumer sharing of assertive and expressive (cf. directive) messages, but this effect switches on Twitter (i.e., word repetition leads to more sharing in combination with expressive acts). The emphasis triggered by word repetition appears to be in sync with Twitter messages, which are brief and straightforward, but at odds with Facebook's longer, more social posts. However, the non-significant joint impact of assertive messages and word repetition on Twitter also suggests that this argument does not hold in all contexts. This exploratory analysis of the joint effects of message content and style thus indicates the critical role of the message context; further fine-grained research should address the interplay of message intentions, figures of speech, and social media platforms.

Third, we contribute to research in social media sharing by addressing the implications of message sequences. Social media brand messages appear as a continuous stream and thus are always received in context, rather than in isolation. In line with Kocielnik and Hsieh (2017), we find that consistently posting the same message type (e.g., assertive followed by another assertive) reduces consumer engagement, whereas complementarity and varied cross-message compositions result in greater message sharing. For example, when brand messages before a focal post exhibit multiple message intentions (e.g., directive preceded by assertive preceded by expressive), consumers share the focal message more. It seems that alternation and novelty in message intentions draw consumers' attention, such that these messages can break through the content clutter of "the same old thing" (Kocielnik and Hsieh 2017). To corroborate this relationship, we also asked a research assistant to code the degree of novelty exhibited by sets of three messages. This coder annotated a random sample of 50 messages containing complementarity (each message used a different speech act) and 50 consistency

(all three messages used the same speech act) sequences from our original data set. The coder indicated the level of originality, unconventionality, and newness across messages (1–9 scale) on Cox and Cox's (1988) measures, and we averaged these three components to obtain a measure of novelty (coefficient $\alpha = .982$). The results show a significantly higher mean novelty rating for the complementarity condition ($M = 6.56$, $SD = 1.49$) than for the consistency condition ($M = 4.69$, $SD = 2.01$; $(F(1,98) = 26.9, p < .001)$). On both Twitter⁷ and Facebook, consistently presenting the same message results in the lowest level of consumer sharing.

Fourth, we offer one of the first large-scale analyses of images in social media. We extend speech act theory by incorporating Kress and van Leeuwen's (2006) conceptualization of image acts. As predicted, and in line with the effects of text, we find that more action images (directives) prompt less sharing of brand messages. This main effect of image acts also corroborates the notion that viewing an image is sufficient to influence behaviors (Poor et al. 2013). Furthermore, considering the joint effect of text and image elements in the same brand message, we find that images create a boundary condition for consumer sharing: Relatively more action-oriented images should be presented in combination with more facilitative (rather than directive) speech acts, to enhance consumer sharing. Emphasizing the same directive goal through both text and images seemingly results in an overbearing form of communication (Petty et al. 2003), leading consumers to tune out. Thus, a combination of more action (directive) images and more facilitating speech acts (assertive or expressive) encourages consumer message sharing, more so than combinations of action images and directive speech acts, which may be overwhelming.

Beyond these four main contributions, our empirical assessment corroborates several

⁷ In analyzing these results, we note that the coefficient for consistency is positive and significant, in contrast with our predictions and the main study findings. During the more than two-year span of our analysis, we thus identify an apparent shift in consumer preferences: For the first year and a half, the coefficient is highly negative, but in the last year, it switched to positive.

results from emerging research on social media (Lamberton and Stephen 2016). Overall, our study affirms research findings regarding the different preferences associated with various social media platforms (Schweidel and Moe 2014). Most of the findings are consistent across Facebook and Twitter, but we also find some significant differences. First, the use of questions increases message sharing on Twitter, but this effect is only marginally significant on Facebook (de Vries et al. 2012), likely reflecting Twitter's more conversational setting, in which questions are valued as a form of interactivity. Second, in line with Berger and Milkman (2012), we find that positive framing enhances message sharing on Facebook, though this effect does not arise on Twitter. To explain this result, we note some organic differences between sites, such that Twitter is more informational (factual), whereas Facebook tends to be more emotional. Furthermore, this finding is consistent with the stronger effect of assertive messages on Twitter, versus the more prominent role of expressive messages on Facebook. Finally, we confirm that the use of pictures has a positive effect on message sharing (de Vries et al. 2012), yet we also note that posts during the weekend significantly reduce message sharing (Cvijikj and Michahelles 2013).

LIMITATIONS AND FURTHER RESEARCH DIRECTIONS

These insights also suggest several alternative routes for testing the implications of language use in brand messages through social media. For example, we control for various factors, but we do not zoom in on the individual interactions that take place between content granularities and different message intentions. This important task is beyond the scope of our article; we encourage further research to deploy our proposed framework to address it.

Researchers could undertake a more detailed analysis of brand messages that combine different message intentions. In our theoretical approach, we assume that when messages have

more than one speech act, the pattern of dominance (directive > expressive > assertive) should lead us to classify it as directive. This assumption takes some variability out of our analysis, so we encourage research that explores its viability. As a first step, we conducted a robustness check to test this assumption⁸ and controlled for brand messages with multiple speech acts. The presence of multiple intentions in a single brand message (e.g., “Everybody loves a good #Rollback! [expressive] Come in now and save on TVs, treats and more [directive]”) has a negative effect on Facebook but a positive one on Twitter—likely because the intrinsically social characteristics of Facebook support more lengthy content, whereas straightforward, concise messages are more common on Twitter.

We study Facebook and Twitter, which are mainly text-based platforms. Although we consider both text and image elements, the implications of our framework might differ on social media channels such as Pinterest and Instagram, where the posts primarily involve pictures or videos (Farace et al. 2017). The vast growth of unstructured image data, and corresponding analytics methods, is a field that will continue to expand, advancing marketing and consumer language research (similar to text mining in recent years). Although our large-scale study offers an initial theoretical and empirical bridge across research into textual and visual communication, continued research is needed to gain a clearer understanding of the interplay of images and text. For example, we find that the presence of readable text in social media images increases sharing, but we do not explore the types of message included in those images. Research on multimodal communication and picture mining (Liu et al. 2017; Mazloom et al. 2016) might offer some relevant insights for further research.

The secondary nature of our data and the design of our empirical studies prevent us

⁸ We selected a subsample of 171 messages from Twitter and Facebook that included two different speech acts. Two independent coders annotated the main intentions within each message, achieving a Cohen’s kappa value of .57 and resolving disagreements through discussion. The consistency between the coders’ annotation and the automatic coding by our algorithm (number of right predictions divided by all predictions) was 69%. We thank an anonymous reviewer for suggesting this analysis.

from specifying potential incongruities between consumers' intentions and the company's goals for sharing messages. Firms might design campaigns for purposes different than those perceived by potential audience, such that consumers might fail to understand the motives of these messages. Examples of social media failures (see <https://awario.com/blog/7-epic-social-media-marketing-fails-not-become-next-one/>) provide anecdotal evidence that communication is a common cause. Some example represent minor misunderstandings, but others are more extreme, such Audi's #PaidMyDues campaign, which focused on drivers instead of cars and sparked huge backlash. Continued research should explore the potential nature and intensity of these incongruities and misunderstandings and how they affect potential outcomes.

Different empirical and analytical research approaches that consider socio-cultural and individual factors also might tap into conceptual differences in figures of speech (McQuarrie and Mick 1996). Their degree of deviation, relative to the expectation of a specific audience, might determine the level of attention and processing and ultimately the impacts on brand message sharing. We used several regular expressions to indicate alliteration and word repetition, but we do not claim to achieve an exhaustive compilation (47% of Facebook posts and 29% of tweets contained at least one of these figures of speech). Furthermore, as we noted previously alliteration is a unidimensional figure of speech, but word repetition can have variations, which might trigger differential effects. Further text mining studies could pursue improved retrieval methods to detect repetition with more granularity (e.g., antimetabole, antithesis, anaphora), as well as mine other rhetorical figures, such as hyperbole, rhymes, metaphors, or irony. The automated classification of rhetorical figures is new, but developments in the detection of other figures of speech will likely reveal novel implications for consumer behavior in social media.

Although we addressed cross-message dynamics (sequences of three messages) from a content perspective, we did not zoom in on optimal timing strategies for these sequences. We

controlled for the average time difference between messages in a sequence, but identifying the optimal timing associated with brand postings was beyond the scope of our investigation.

Leveraging studies of message frequency (Stephen et al. 2017), further research could explore the time dispersion across messages and the impact on sequence effectiveness. For example, an important brand event (e.g., product launch) could benefit from greater message frequency, but periods without major brand events might require lesser frequency and greater time dispersion.

Other brand communication contexts, beyond brand-generated content, also might provide interesting replication opportunities. For example, in online chats, commissive speech acts commonly are performed by customer service providers, who issue promises in response to customer demands (e.g., “We will get back to you within 24 hours”). Widening the application of our framework to such contexts might contribute to the development of the field, from both theoretical and practical perspectives.

This article offers an empirical assessment of consumers’ sharing of social media brand messages. Using text mining and image annotation, we offer an innovative approach to content marketing in social media; with its focus on aggregated engagement outcomes (e.g., retweet counts), this approach also may be relevant for consumer research more broadly. Experimental studies (ideally, field studies) conducted in collaboration with content managers could assess the effectiveness of different content strategies, provide more granular insights into individual consumer behavior, and delineate the psychological mechanisms that drive consumer sharing in social media.

IMPLICATIONS

Consumers have a pivotal role in distributing social media brand content through their message sharing (Napoli 2009). However, as more brands join online conversations and content expands, it becomes harder to capture people's attention and engage consumers in the active distribution of branded content. The managerial focus thus has shifted, toward compositional issues, as they relate to individual traits and message streams, and ways to ensure brand content gets shared through social media (Jukowitz 2014). Using this departure point, we offer four insights into how and when consumers are more likely to share brand messages, as well as which messages they tend to share.

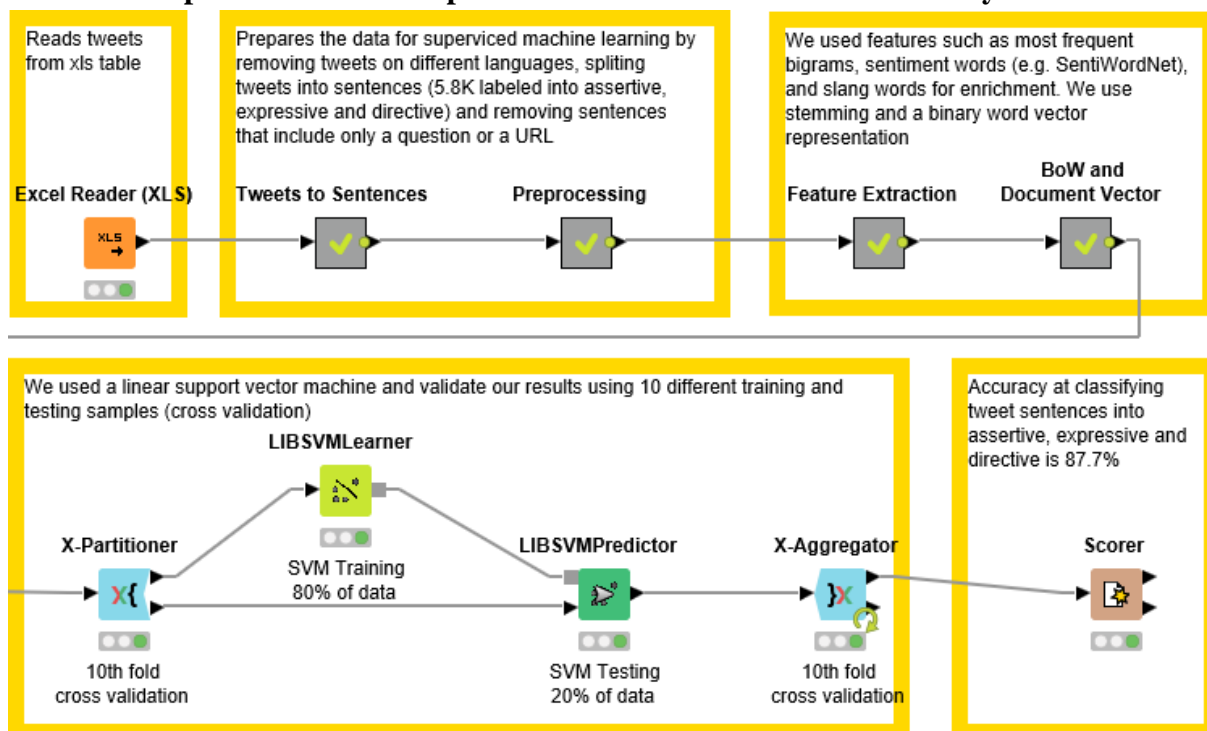
First, consumers are more willing to share brand messages with informational or emotional content, rather than demands or commands. Yet most online brand messages call on consumers to execute an action (e.g., "Come to our event Friday!"). Brands instead should adapt their social media language and open their communication with informational (e.g., "We have a new product launch this Friday") or emotional (e.g., "Fridays are fun") phrases. Second, stylistic message properties must be used strategically, according to the social network. Facebook represents more of an advertising-oriented social network, so rhetorical devices are more likely to result in engagement. On Twitter, explicit advertising cues (e.g., directive messages, including repetition or alliteration) will turn consumers' attention elsewhere. Third, consumers' uses of social media are dynamic, so brands must consider each single message according to the specific sequences or communication streams in which it appears. The preceding presence of assertive or expressive messages increases subsequent sharing of directive messages; managers therefore should take advantage of the benefits of complementary sequences, rather than posting the same message type consistently. Fourth, our study provides insights into the use of visuals. Content managers should combine different intentions at the text and image levels, because action images in combination with assertive or

expressive messages will result in greater engagement than action images with directive messages, which instead overburden consumers.

In summary, this study demonstrates the importance of considering linguistic markers to understand the phenomenon of social message sharing by consumers. Using SAT as an enabling framework, we confirm that message intentions (speech acts), style (rhetoric), dynamics (sequences), and visuals (image acts) contribute to the structure and sharing of social media brand communication. Our research delineates and validates general cues at each level; SAT accordingly provides relevant guidelines for extending the study of C2C sharing to message intentions, figures of speech, dynamics, and images. These insights on consumer online sharing may guide firms learning how to speak, write, text, and post in the language of their consumers, so that they may more effectively join social media conversations.

Appendix

A. Example Workflow for Speech Act Classification in Knime Analytics



This workflow represents an annotated visual representation of the machine learning process to automate the classification of tweet sentences into message intentions. The process starts with an Excel reader, which fetches the sample of tweets. Then we split these tweets into sentences and asked two coders to annotate them as assertive, expressive, or directive. The machine learning process starts with “Preprocessing,” to clean the data by removing sentences that include only a URL, hashtag, or question (using regular expressions). The “Feature Extraction” step (Zhang et al. 2011) selected words that function as predictors or support vectors to replicate the coders’ classification. We used the stem forms of these words to avoid semantic duplication. The resulting bag of words consisted of 56,674 unique predictor words, which we converted into a document vector in which each sentence is represented by its combination of unique words (1 = word is present, 0 = word is not present). We used support vector machines (SVM) as the classification algorithm (Zhang et al. 2011). The coded tweet sentences then were split into training (SVM learner) and testing (SVM predictor) samples. We used 80% of the coded sentences as the training sample to develop the SVM algorithm that automated the classification of message intentions based on the vectors (words). Testing occurred with the remaining 20% of the data (holdout sample). Finally, we applied the scorer node to assess the accuracy of the model for the holdout sample.

B. Regular Expressions Used to Capture Alliteration

Consonants	Vocals	Multiple Sounds
\bb\w+\s\bb\w+	\ba\w+\s\ba\w+	(\bf\w+\ bph\w+)\s(\bf\w+\ bph\w+)
\bc\w+\s\bc\w+	\be\w+\s\be\w+	(\bc\w+\ bk\w+)\s(\bc\w+\ bk\w+)
\bd\w+\s\bd\w+	\bi\w+\s\bi\w+	(\bye\w+\ bje\w+\ bge\w+)\s(\bye\w+\ bje\w+\ bge\w+)
\bf\w+\s\bf\w+	\bo\w+\s\bo\w+	(\bce\w+\ bs\w+)\s(\bce\w+\ bs\w+)
\bg\w+\s\bg\w+	\bu\w+\s\bu\w+	
\bh\w+\s\bh\w+		
\bj\w+\s\bj\w+		
\bk\w+\s\bk\w+		
\bl\w+\s\bl\w+		
\bm\w+\s\bm\w+		
\bn\w+\s\bn\w+		
\bp\w+\s\bp\w+		
\bqu\w+\s\bqu\w+		
\br\w+\s\br\w+		
\bs\w+\s\bs\w+		
\bt\w+\s\bt\w+		
\bv\w+\s\bv\w+		
\bw\w+\s\bw\w+		
\bx\w+\s\bx\w+		
\by\w+\s\by\w+		
\bz\w+\s\bz\w+		
\bch\w+\s\bch\w+		

Excluded
.*\bt\w+\s\bth\w+.*
.*\bth\w+\s\bt\w+.*
.*\bsh\w+\s\bs\w+.*
.*\bs\w+\s\bsh\w+.*
.*\bce\w+\s\bk\w+.*
.*\bk\w+\s\bce\w+.*
.*\bci\w+\s\bk\w+.*
.*\bk\w+\s\bci\w+.*
.*\bch\w+\s\bc\w+.*
.*\bc\w+\s\bch\w+.*
(\bce\w+\ bsh\w+)\s(\bce\w+\ bsh\w+)

C. Robustness Check using Likes (Favorites) as a Dependent Variable on Models 3 and 6

DV: Likes/Favorites	Model 3		
Variables	Facebook		Twitter
Lag Share Count	0.00		0.00 **
D. Assertive	0.71 †		2.96 **
D. Expressive	4.09 **		-0.40
Alliteration	0.17 **		-0.47 **
Repetition	0.40 **		0.00
Assertive * Allit.	-0.30		0.00
Assertive * Rep.	-0.16 **		-0.01
Expressive * Allit.	-0.08		0.16 **
Expressive * Rep.	-0.36 **		0.13
Sequence Concentration	-0.17 **		-0.30 **
Multiple Intentions	-0.01		0.37 **
Time difference	0.00 **		0.00
Positivity	0.09 **		0.06 *
Question	0.30		-0.10
Hour	-0.00		0.00
Weekend	-0.11 **		0.01
Hashtag	0.23 *		-0.32 **
Share from other	0.05		0.43 **
Picture	0.48 †		-2.46 **
Video	0.76 **		-0.25 *
Link	0.17		0.62 **
Album	-2.07 **		
Intercept			
Log likelihood	-9224		-169788
Sample size	12,102		29,413

† $p < .1$, * $p < .05$, ** $p < .01$.

DV: Likes/Favorites	Model 6		
Variables	Facebook		Twitter
Lag Share Count	0.00		0.00 **
D. Assertive	0.78		-2.30 **
D. Expressive	6.15 **		3.12 **
Alliteration	-0.34 *		-0.00
Repetition	0.29		-0.12
Assertive * Allit.	0.16 †		-0.03
Assertive * Rep.	0.01		0.04
Expressive * Allit.	-0.35 **		-0.27 **
Expressive * Rep.	0.15		0.62 **
Sequence Concentration	-0.25 †		0.19 **
Information Action (IA)	-0.03		-0.02 **

IA * Assertive	0.01		0.01	
IA * Expressive	0.04		0.05	*
Multiple Intentions	-0.36	**	0.35	
Time difference	0.00		0.00	
Text on Image	-0.09	†	0.06	**
Positivity	-0.11		-0.03	
Question	-0.37		-2.46	**
Hour	0.01	**	-0.01	**
Weekend	-0.35	**	-0.12	**
Hashtag	0.08		-0.61	**
Share from other	-0.47	**		
Picture	0.81		-0.04	
Video				
Link			-0.10	
Album	-3.41	**		
Intercept	5.01	**	7.46	**
Log likelihood	-17640		-438620	
Sample size	2,214		6,996	

† $p < .1$, * $p < .05$, ** $p < .01$.

DATA COLLECTION INFORMATION

The first author collected the Facebook data using the Facebook API and supervised the data collection from Twitter using a third-party organization from UpWork. All the data analysis in Study one and two was performed by the first author. The annotation of images of Study two was executed by professional image annotators from Upwork and supervised by the first author.

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Table 1
SAMPLE DESCRIPTION

Brand	Industry	Facebook Total Messages (Average per Day)	Twitter Total Tweets (Average per Day)
Disney	Hospitality	5,062 (5.4)	6,382 (6.8)
Amazon	Retail trade, miscellaneous	3,856 (4.1)	8,739 (9.4)
Tesco	Retail trade, department & convenience stores	946 (1.01)	3,963 (4.27)
McDonalds	Retail trade, eating & drinking places	720 (.7)	966 (1.04)
Walmart	Retail trade, department & convenience stores	598 (.65)	1,196 (1.3)
Coca Cola	Food	547 (.6)	2,777 (3)
Ford	Manufacturing	530(.6)	1,833 (2)
Nike	Retail trade, apparel & accessory stores		3,560 (3.8)

Table 2**SUPPORT VECTOR MACHINE SPEECH ACT CLASSIFICATION RESULTS**

	Recall	Precision	F
Assertive	.93	.802	.861
Expressive	.36	.818	.5
Directive	.928	.948	.938
Notes: 10-fold cross validation results. Accuracy = 87.7%.			

Table 3

**MEANS, STANDARD DEVIATIONS, AND CORRELATIONS ON FACEBOOK (LOWER DIAGONAL) AND TWITTER
(UPPER DIAGONAL)**

	Variable	Mean	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1	retweetCount	516.64	4605.28	1.00	0.00	0.03	-0.02	0.05	-0.03	0.01	-0.01	0.00	0.02	-0.05	0.00	0.01	0.00	-0.05	0.10	-0.11	0.05
2	D_Assertive	0.45	0.50	0.00	1.00	-0.22	-0.90	-0.38	-0.05	0.02	0.02	0.01	-0.07	-0.10	0.00	0.01	-0.01	0.03	0.01	-0.08	-0.14
3	D_Expressive	0.06	0.24	0.02	-0.23	1.00	-0.22	0.11	0.00	0.01	-0.22	0.00	0.16	-0.03	0.01	0.01	0.03	-0.04	0.03	-0.13	-0.03
4	D_Directive	0.49	0.50	-0.01	-0.89	-0.25	1.00	0.33	0.05	-0.03	0.07	-0.02	0.00	0.11	0.00	-0.01	0.00	-0.01	-0.03	0.13	0.16
5	Multiple Speech Acts	0.22	0.42	0.01	-0.49	0.05	0.46	1.00	0.02	-0.01	-0.08	0.01	0.05	-0.08	0.03	-0.01	0.11	-0.13	0.08	-0.03	0.10
6	Alliteration	0.51	0.75	0.00	-0.11	0.00	0.11	0.20	1.00	0.01	-0.02	-0.01	0.06	0.02	-0.03	-0.01	-0.14	0.00	0.00	0.06	-0.02
7	Repetition	0.20	0.54	-0.01	-0.04	-0.01	0.05	0.06	0.08	1.00	-0.03	0.00	0.01	0.00	0.02	-0.01	-0.01	-0.03	0.00	-0.03	0.02
8	Consistency	0.66	0.21	-0.02	0.02	-0.22	0.08	0.06	0.00	0.01	1.00	-0.01	-0.09	-0.08	-0.07	0.03	-0.09	0.08	-0.08	0.10	0.03
9	Time difference avg.	312.60	2529.19	0.00	-0.03	0.02	0.02	0.02	0.04	0.00	-0.01	1.00	0.01	0.01	-0.03	-0.02	0.03	-0.03	0.02	-0.04	-0.01
10	Positivity	1.85	0.39	0.02	-0.21	0.12	0.16	0.08	0.12	0.06	-0.17	0.00	1.00	0.03	0.00	0.03	-0.02	-0.02	0.01	-0.02	0.01
11	Question	0.16	0.37	-0.01	-0.11	-0.04	0.13	0.03	0.06	-0.01	0.00	0.01	0.05	1.00	-0.01	0.00	0.07	-0.08	-0.02	-0.05	0.00
12	Hour	15.00	6.69	-0.01	-0.01	0.00	0.01	-0.02	-0.02	0.01	0.00	0.01	-0.01	0.01	1.00	-0.10	0.10	-0.06	0.05	-0.02	0.07
13	Weekend	0.16	0.37	0.00	-0.02	0.02	0.01	0.03	-0.02	-0.03	0.00	-0.02	0.02	0.01	-0.11	1.00	-0.05	0.03	-0.01	-0.03	-0.05
14	Hashtag	0.15	0.39	-0.02	-0.07	0.00	0.07	0.17	0.00	0.02	0.00	0.02	0.05	0.13	0.00	-0.01	1.00	-0.22	0.10	-0.14	0.14
15	Picture	0.38	0.49	-0.02	0.04	0.05	-0.07	0.05	-0.05	-0.04	0.03	-0.01	-0.20	0.12	-0.03	0.13	0.13	1.00	-0.58	0.23	-0.09
16	Video	0.21	0.40	0.10	-0.07	0.00	0.07	0.16	0.04	-0.02	-0.03	0.05	0.04	-0.02	-0.07	0.05	0.06	-0.40	1.00	-0.13	-0.05
17	URL	0.38	0.49	-0.06	0.03	-0.05	-0.01	-0.21	-0.01	0.04	-0.01	-0.03	0.16	-0.14	0.08	-0.17	-0.19	-0.61	-0.40	1.00	-0.07
18	Share from other	0.02	0.13	-0.01	0.04	-0.01	-0.04	-0.02	-0.03	-0.03	0.01	0.01	-0.14	-0.04	-0.01	0.00	0.00	-0.03	0.17	-0.10	1.00
19	Album	0.02	0.14	-0.02	0.16	-0.04	-0.14	-0.08	-0.10	-0.05	0.18	-0.01	-0.69	-0.06	0.02	0.00	-0.06	0.19	-0.07	-0.11	-0.02

Table 4
MAIN STUDY RESULTS

DV: SHARE COUNT	Model 1				Model 2				Model 3			
	FBK		TW		FBK		TW		FBK		TW	
Model Variables												
Lag share count	0.00		0.00	**	0.00		0.00	**	0.00		0.00	**
D. assertive	-0.58		3.10	**	-0.06		2.78	**	0.02		2.84	**
D. expressive	8.99	**	2.819	**	8.77	**	1.97	**	8.59	**	1.45	**
Alliteration (All)					-0.14	†	-0.80	**	-0.13		-0.75	**
Repetition (Rep)					0.65	**	-0.03		0.66	**	-0.03	
All * Assertive					-0.04		0.21	**	-0.04		0.19	**
Rep * Assertive					-0.15	**	0.02		-0.15	**	0.02	
All * Expressive					0.18	*	0.62	**	0.18	*	0.61	**
Rep * Expressive					-0.73	**	0.39	**	-0.74	**	0.39	**
Sequence consistency									-0.17	**	-0.37	**
Multiple intentions	-0.20	**	0.16	**	-0.19	**	0.19	**	-0.18	**	0.19	**
Time difference									0.00	†	0.00	
Positivity	0.43	**	-0.01	**	0.45	**	0.02		0.45	**	0.01	
Question	0.40		0.59	†	0.74		1.05	**	0.84	†	0.92	**
Hour	0.000		-0.01	**	0.00		-0.01	**	0.00		-0.01	**
Weekend	-0.15	**	-0.09	**	-0.15	**	-0.1	**	-0.14	**	-0.09	**
Hashtag	-0.60	**	-0.44	**	-0.59	**	-0.50	**	-0.59	**	-0.44	**
Share from other	-4.92	**	1.57	**	-4.93	**	1.55	**	-4.92	**	1.58	**
Image	2.66	**	0.50	**	2.47	**	0.56	**	2.48	**	0.57	**
Video	3.93	**	-0.4	†	3.63	**	-0.33	†	3.59	**	-0.45	*
Link	4.29	**	-0.7		3.99	**	-0.60	**	4.02	**	-0.64	**
Album	-2.03	**			-1.99	**			-1.98	**		
Intercept	-0.90	*	3.01	**	-1.12	*	3.23	**	-1.08	*	3.54	**
Log likelihood	-69238		-151244		-69195		-150948		-69190		-150886	
Sample size	12,102		29,413		12,102		29,413		12,102		29,413	

† $p < .1$.

* $p < .05$.

* $p < .01$.

Notes: We do not report the coefficients for the residual functions and brand fixed effects, for parsimony.

Table 5
IMAGES PER BRAND

	Facebook		Twitter	
	Picture	Video	Picture	Video
Disney Parks	862	27	5546	18
Amazon	2267	831	6892	616
Tesco	496	332	2463	398
McDonalds	511	109	392	340
Walmart	288	242	732	66
Coca Cola	7	71	2118	160
Ford	266	205	825	315
Nike Store			3395	88

Table 6
EXTENDED STUDY RESULTS

DV: SHARE COUNT	Model 4				Model 5				Model 6			
	FBK		TW		FBK		TW		FBK		TW	
Model Variables												
Lag share count	0.00		0.00	**	0.00		0.00	**	0.00		0.00	**
D. assertive	-0.31	**	-3.83	**	-0.29		-3.72	**	-0.38		-3.86	**
D. expressive	8.89	**	3.94	**	9.15	**	3.99	**	9.30	**	3.58	**
Alliteration (All)	-0.84	**	0.05		-0.82	**	0.08		-0.81	**	0.08	
Repetition (Rep)	-0.16		-0.45	**	-0.18		-0.42	*	-0.22		-0.4	*
Assertive * All.	-0.02		0.08	†	-0.01		0.06		0.03		0.06	
Assertive * Rep.	0.28	*	0.12	†	0.25	*	0.10		0.26	*	0.09	
Expressive * All.	-0.29	*	-0.17		-0.31	*	-0.22	†	-0.29	*	-0.2	†
Expressive * Rep.	-0.34		1.12	**	-0.30		0.96	**	-0.33		1.06	**
Sequence consistency	-0.52	**	0.19	**	-0.52	**	0.18	**	-0.52	**	0.18	**
Information action (IA)					-0.02		-0.04	**	-0.07	**	-0.07	**
IA * Assertive									0.09	*	0.04	**
IA * Expressive									0.12	†	0.13	**
Multiple intentions	-0.53	**	-0.18	**	-0.56	**	-0.20	**	-0.55	**	-0.17	**
Time difference	0.00		0.00		0.00		0.00		-0		0.00	
Text on image					0.20	**	0.30	**	0.20	**	0.30	**
Positivity	0.19	†	-0.10		0.24	**	-0.04		0.24	**	-0.06	
Question	-1.16		-3.08	**	-3.15		-2.74	**	-3.3		-2.73	**
Hour	0.03	**	-0.04	**	0.03	**	-0.04	**	0.03	**	-0.04	**
Weekend	-0.39	**	-0.23	**	-0.37	**	-0.21	**	-0.35	**	-0.21	**
Hashtag	-0.92	*	-1.06	**	1.02	*	-0.99	**	0.99	*	-1.00	**
Share from other	-6.54	**	0	**	-6.46	**			-6.46	**		
Image	2.05	**	-0.02		1.94	**	0.18		2.01	**	0.21	
Link			0.18				0.26				0.244	
Album	-3.51	**			-3.32	**			-3.3	**		
Intercept												
Log likelihood	-13295		-36826		-13291		-36749		-13287		-36737	
Sample size	2,214		6,996		2,214		6,996		2,214		6,996	

† $p < .1$.* $p < .05$.* $p < .01$.

Notes: Empty cells indicate an omitted variable (e.g., in model 4, all observations with images included a link). We do not report the coefficients for the residual functions and brand fixed effects, for parsimony.

Table 7
Summary of Results

		Hypotheses & Explorations	Facebook	Twitter
Main Study	H ₁	Assertive & Expressive > Directive	Partially Supported	Supported
	RQ ₁	β Alliteration * Assertive	ns	> 0
		β Alliteration * Expressive	> 0	> 0
	RQ ₁	β Repetition * Assertive	< 0	ns
		β Repetition * Expressive	< 0	> 0
	H ₂	β Consistency < 0	Supported	Supported
Extended Study	H ₃	β Information Action < 0	Supported	Supported
	H ₄	β Information Action * Assertive > 0	Supported	Supported
		AND β Information Action * Expressive > 0		

Figure 1

EXAMPLES OF ANNOTATED IMAGES REPRESENTING INFORMATION AND ACTION

Information



Action



Figure 2
EXAMPLE IMAGES WITH READABLE TEXT



HEADINGS LIST

1. CONCEPTUAL BACKGROUND

1. HYPOTHESES

- 2. Implications of Speech Acts for Consumer Sharing
- 2. Joint Implications of Speech and Rhetoric for Consumer Sharing
- 2. Implications of Cross-Message Speech Acts for Consumer Sharing
- 2. Image Acts and Consumer Sharing
- 2. Joint Implications of Speech and Image Acts

1. INTENTIONS, STYLE, AND SEQUENCES IN POST AND TWEET STUDIES

- 2. Research Setting
- 2. Measures
- 2. Control Measures
- 2. Model Specifications
- 2. Hypotheses Tests

1. SPEECH AND IMAGE ACTS, STUDY EXTENSION

1. DISCUSSION

1. LIMITATIONS AND FURTHER RESEARCH DIRECTIONS

1. IMPLICATIONS